Universität
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Real Time Freshness Detection for Plant Harvesting

Final Project Presentation

Group 1

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Date: 30 September 2024

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- Workflow
- Machine Learning Model Architecture
- Dataset, Training and Evaluation Results
- Demonstration and Detection Result
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Introduction

- **PROBLEM STATEMENT:** Freshness of a Plant before harvesting is essential for agricultural and food supply chain quality control, but the traditional methods are inefficient and time consuming.

- **SOLUTION:** Hereby we propose a solution with ML based Edge Computing system to increase production quality, quantity and move towards zero-wastage. Edge computing provides an ideal solution by enabling local, on-device image classification without relying on internet connectivity and are highly scalable.

- **PLANT SELECTION:** MINT PLANT

<u>UN's Sustainable Development Goals (SDG):</u>

Zero Hunger: The proposed solution contributes to improving food security by ensuring that agricultural products (like mint leaves) are monitored for freshness. This could help reduce food waste, ensure timely harvesting, and enhance food quality, all of which support sustainable agricultural practices and food availability.
Responsible Consumption and Production: The proposed solution promotes efficient resource use by preventing the spoilage of leaves and other agricultural products. By ensuring leaves are consumed or used at their freshest and also dry leaves packaging, helping to minimize waste, which is a key aspect of responsible consumption and sustainable production

Hardware setup

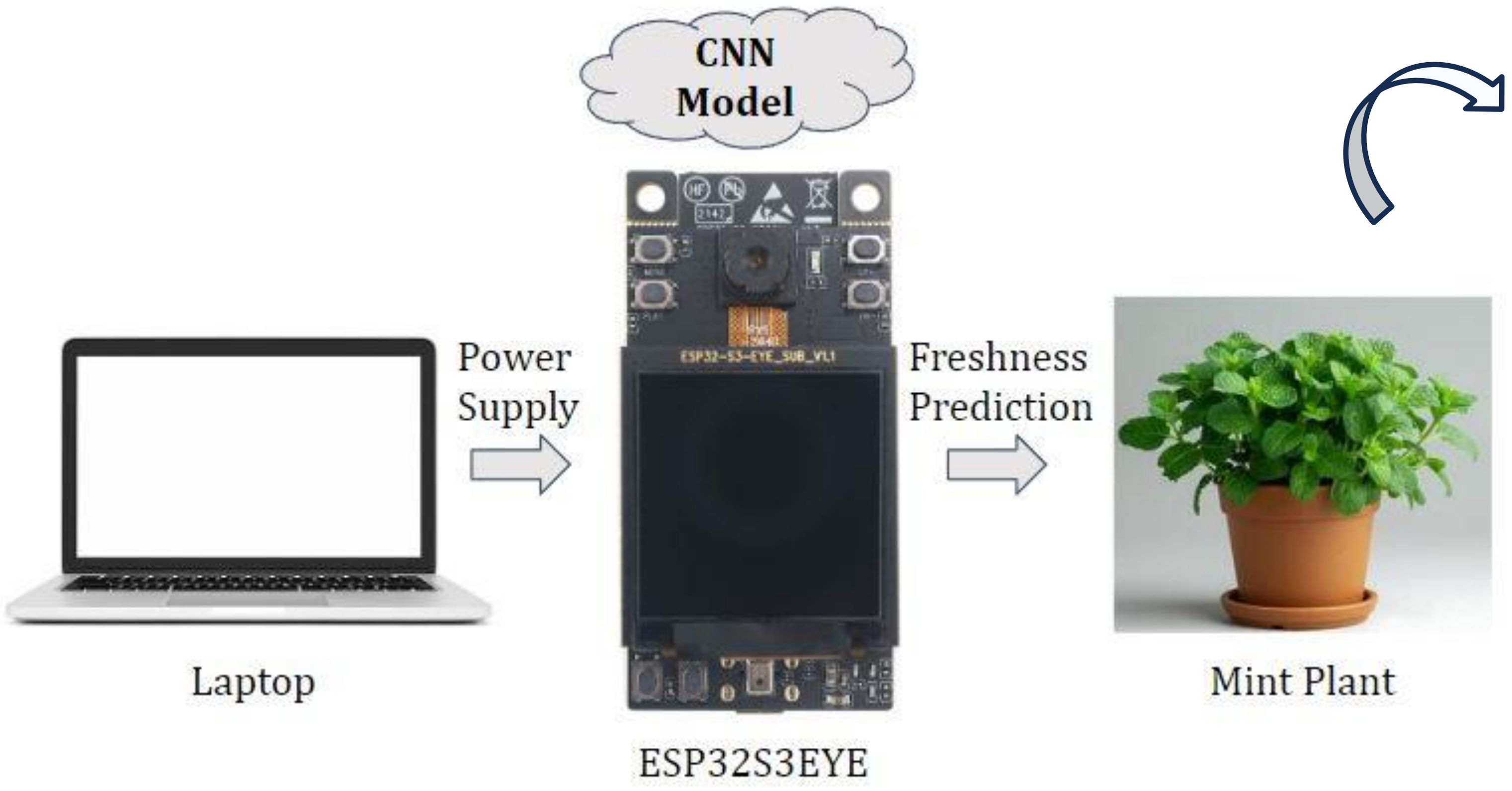


Fig 1: Setup Block Diagram

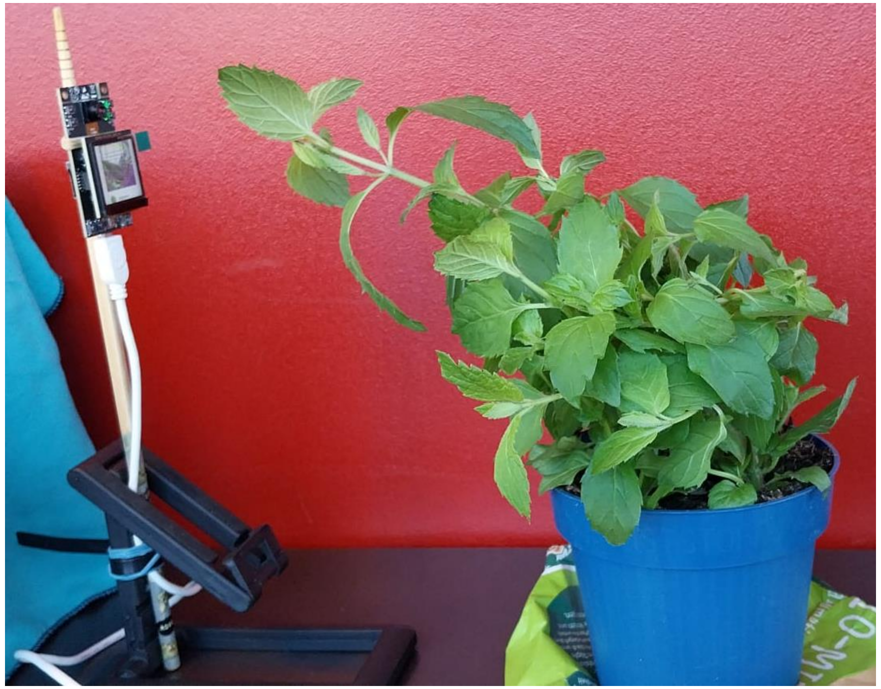


Fig 2: Hardware Setup

Workflow

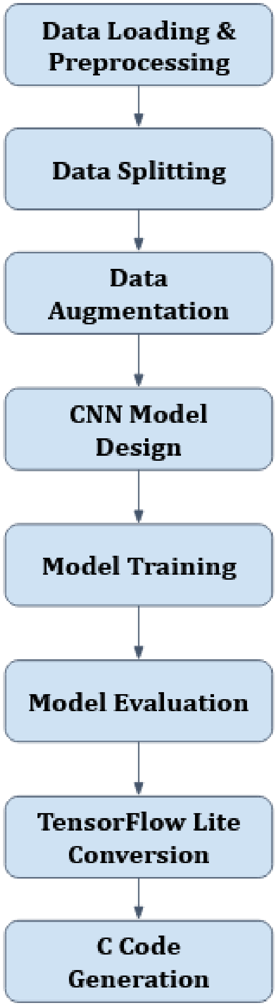


Fig 3: Workflow (Training)

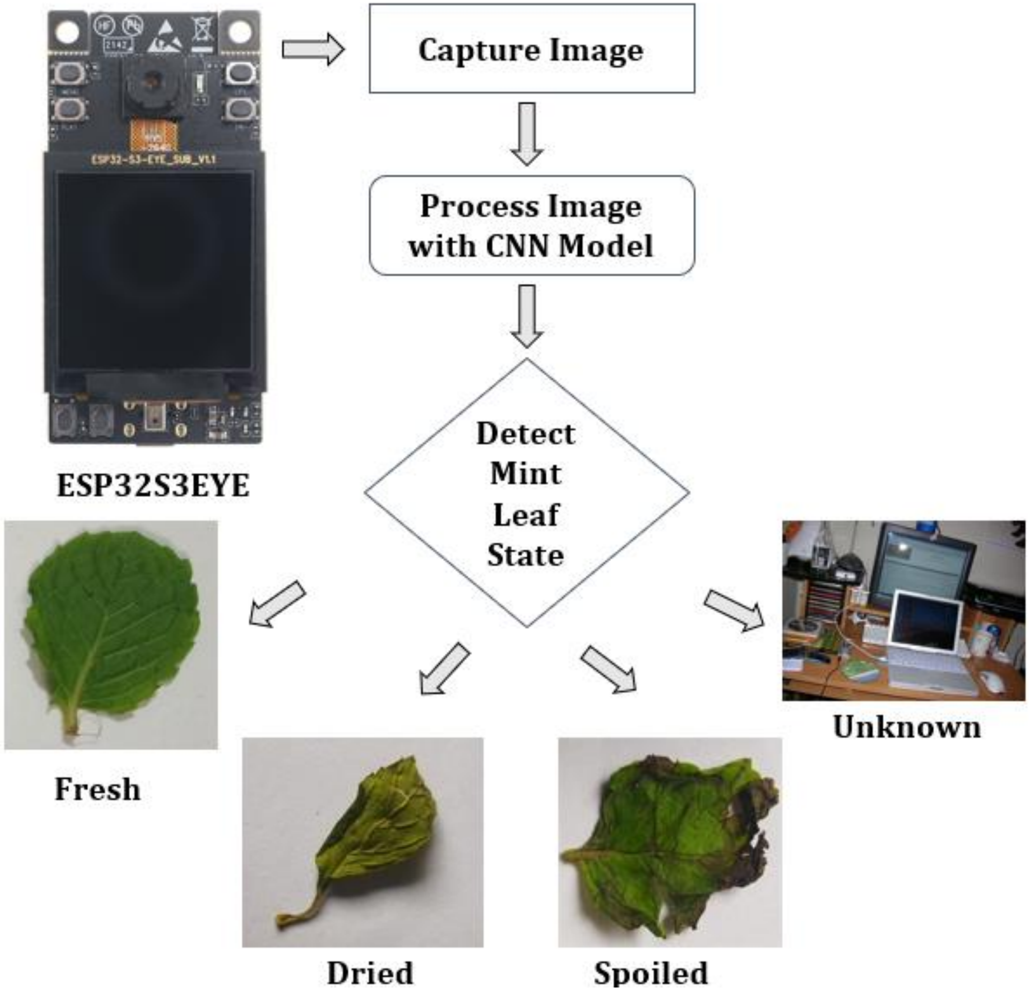


Fig 4: Workflow (Detection)

Machine Learning Model

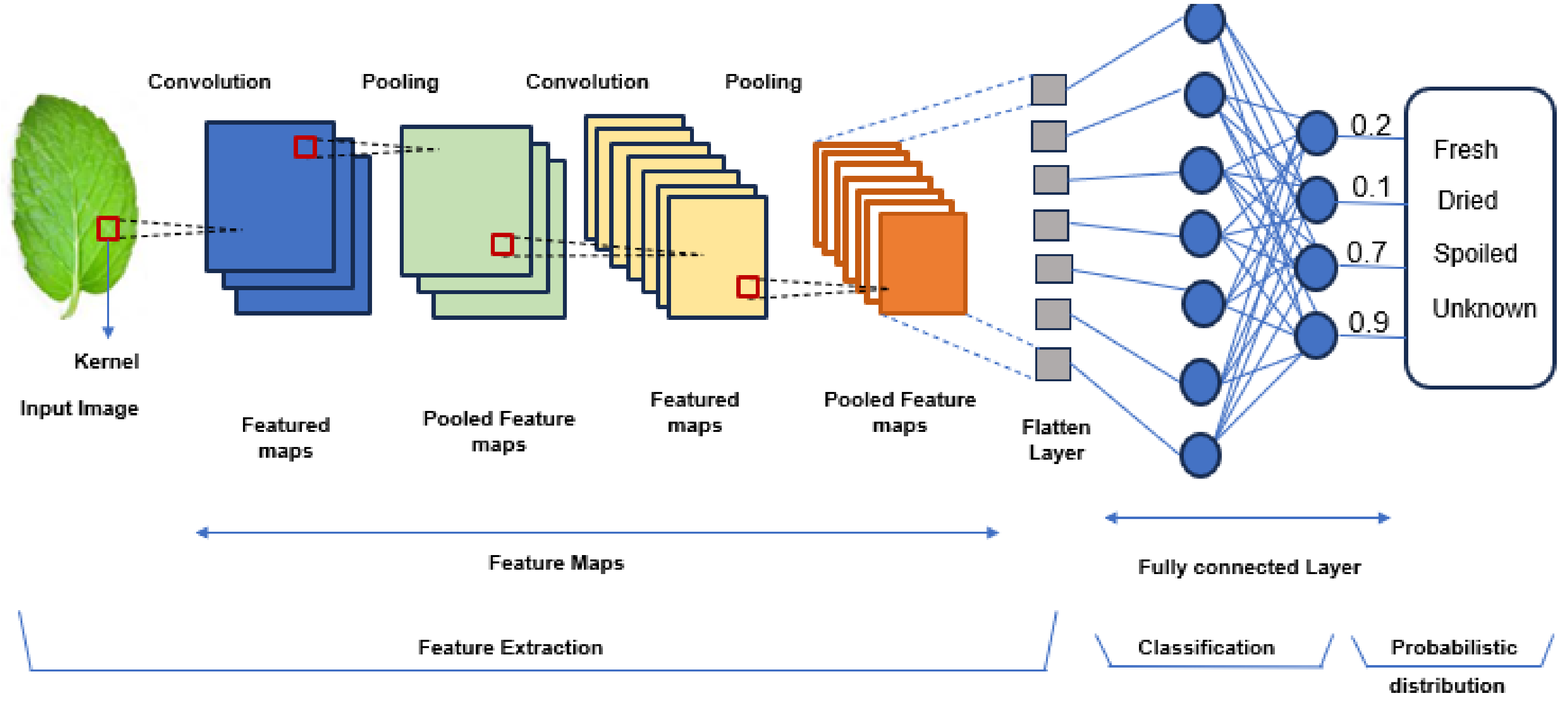
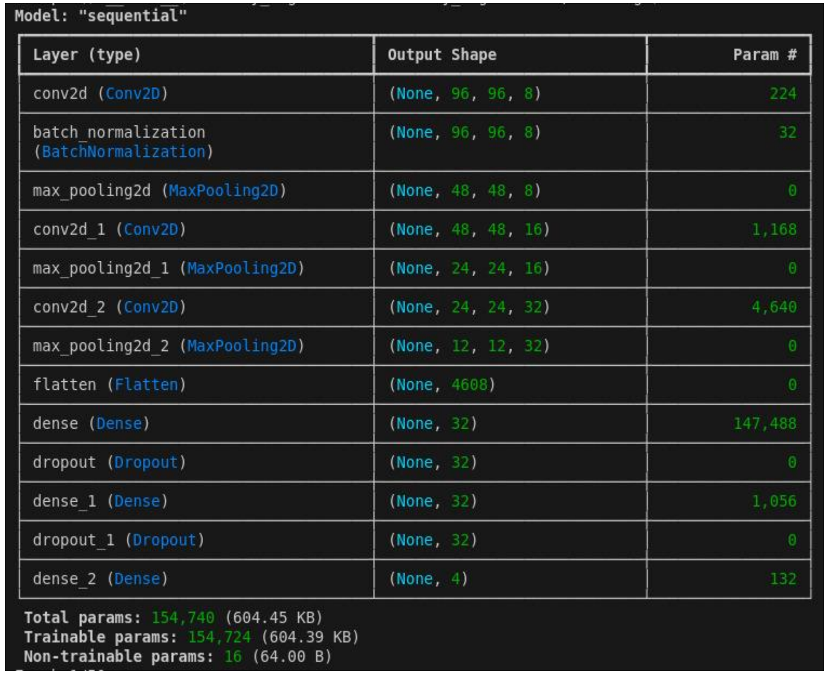


Fig 5: Model architecture of a Typical Convolution Layer



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 96, 96, 8)	224
batch_normalization (BatchNormalization)	(None, 96, 96, 8)	32
max_pooling2d (MaxPooling2D)	(None, 48, 48, 8)	0
conv2d_1 (Conv2D)	(None, 48, 48, 16)	1,168
max_pooling2d_1 (MaxPooling2D)	(None, 24, 24, 16)	0
conv2d_2 (Conv2D)	(None, 24, 24, 32)	4,640
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 32)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 32)	147,488
dropout (Dropout)	(None, 32)	0
dense_1 (Dense)	(None, 32)	1,056
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 4)	132

Total params: 154,740 (604.45 KB)
Trainable params: 154,724 (604.39 KB)
Non-trainable params: 16 (64.00 B)

Fig 6: Convolution Model Summary used in this application

Dataset

	Fresh	Dried	Spoiled	Unknown
Training	1699	1699	1699	1699
Testing	170	170	170	170
Validation	170	170	170	170

Fig 7: Dataset Details for Training, Test & Validation for each category

Performance Metrics	
Accuracy	0.9105
Precision	0.9269
Recall	0.9105
F1 Score	0.9115

Fig 9: Performance Matrix based on Confusion Matrix

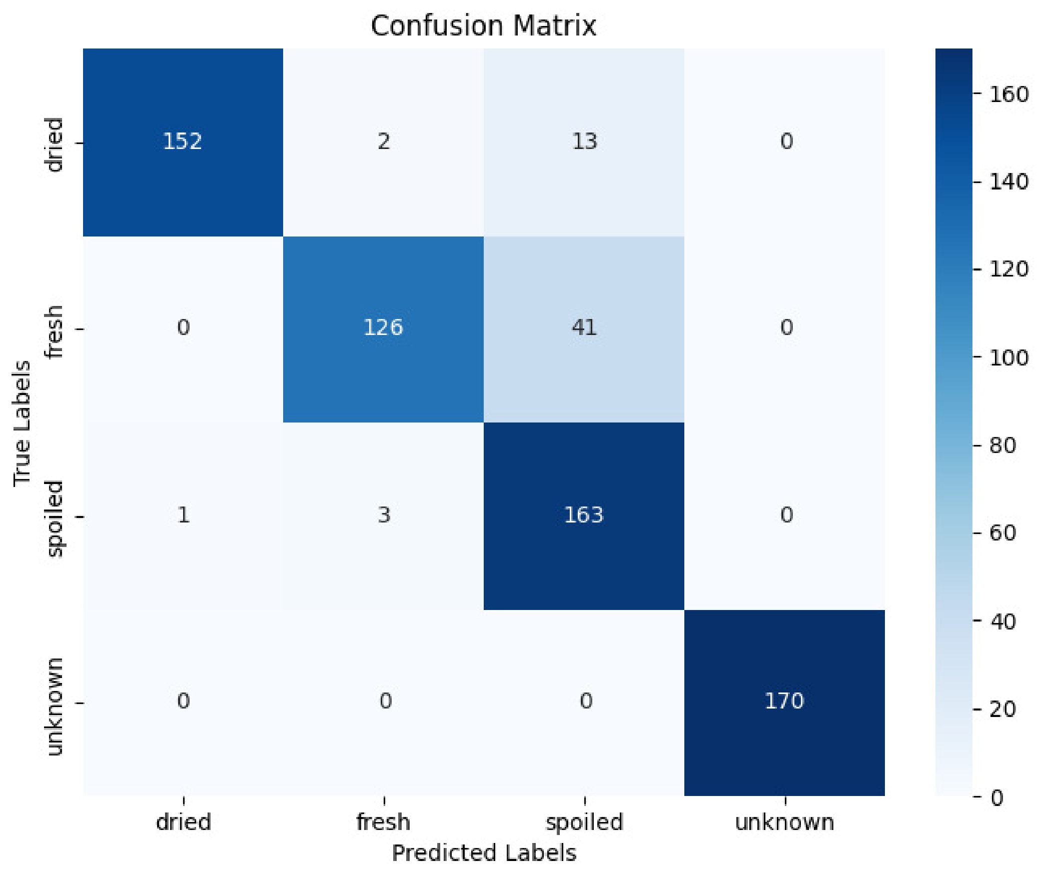


Fig 8: Confusion Matrix

Training and Evaluation Results

Fig 10: Data Augmented input images with Label

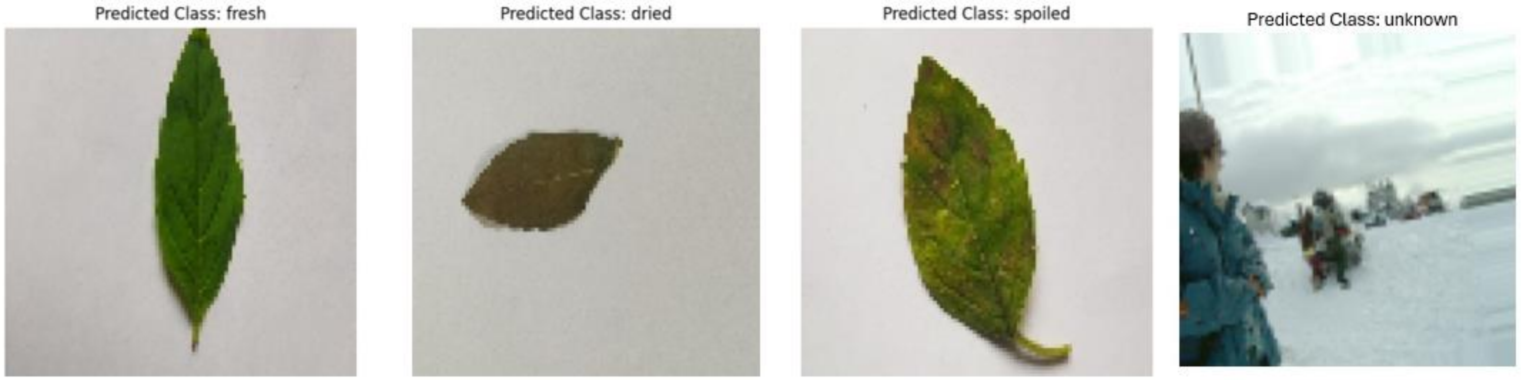


Fig 11: Sample Predictions using the generated Model

Training and Evaluation Results

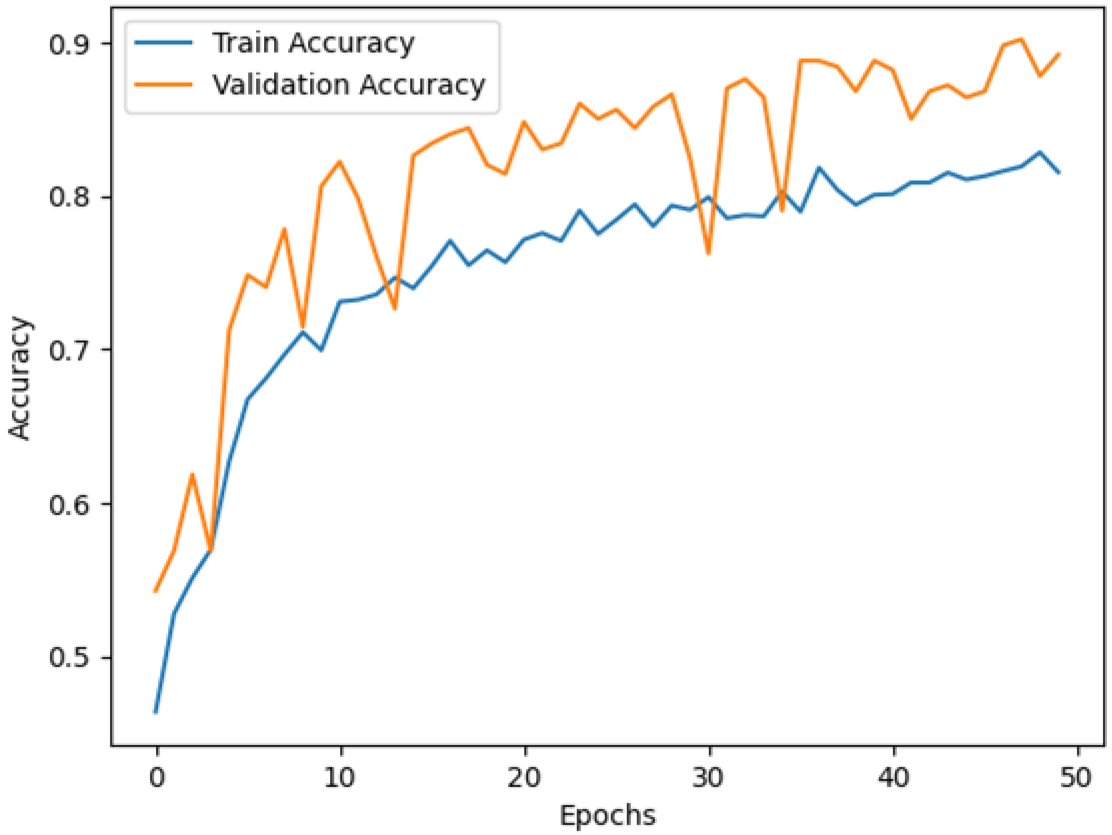


Fig 12: Plot showing Train vs Validation accuracy for corresponding epoch

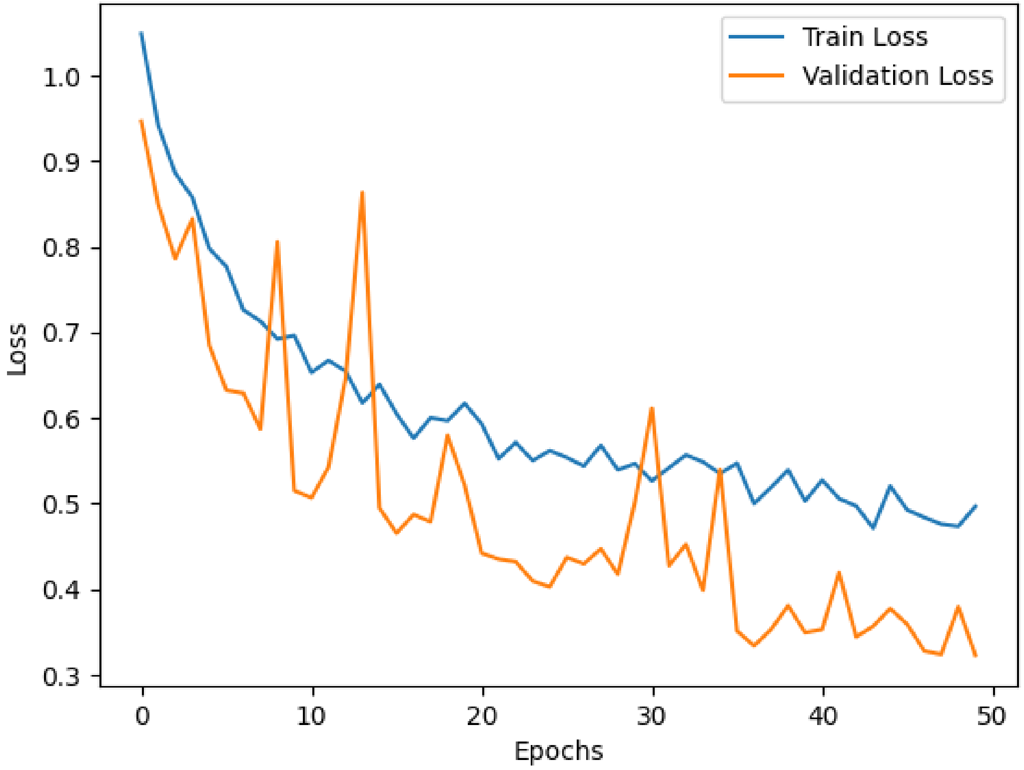
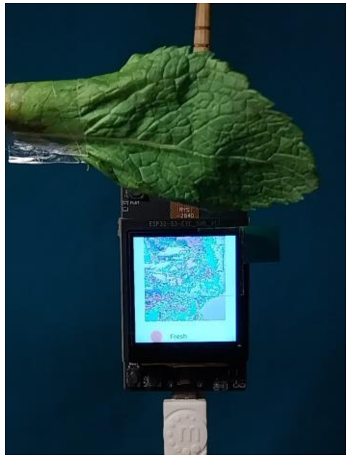


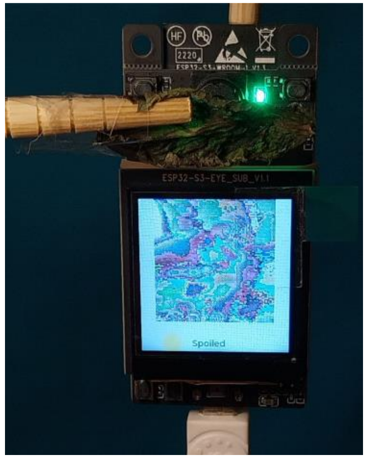
Fig 13: Plot showing Train vs Validation loss for corresponding epoch

Device Demonstration & Detection Result



Detection: Fresh

Detection: Dried



Detection: Spoiled

Detection: Unknown

```
fresh score: 0%, dried score: 0%, spoiled score: 0%, unknown score: 0%
fresh score: 43%, dried score: 12%, spoiled score: 12%, unknown score: 12%
fresh score: 2%, dried score: 92%, spoiled score: 5%, unknown score: 5%
fresh score: 2%, dried score: 93%, spoiled score: 5%, unknown score: 5%
fresh score: 7%, dried score: 79%, spoiled score: 13%, unknown score: 13%
fresh score: 11%, dried score: 71%, spoiled score: 15%, unknown score: 15%
fresh score: 8%, dried score: 67%, spoiled score: 11%, unknown score: 11%
fresh score: 10%, dried score: 60%, spoiled score: 10%, unknown score: 10%
fresh score: 0%, dried score: 0%, spoiled score: 0%, unknown score: 0%
```

Serial Port Output

Fig 14: Detection Result of Mint leaves for various categories on LCD and serial port

Problems Faced & Foreword Prospect

- **MACHINE LEARNING MODEL:** Simpler Model architecture to support hardware - the accuracy of the model not so great – Dataset variety and quantity
- **DATASET :** some amount of false positive were observed more in Dried and Spoiled specimen
- **INDOOR DETECTION:** Since indoor environmental conditions are controlled, the dataset trained for indoor environment was not complex as when compared with outdoor
- **ONLY ONE POINT DETECTION:** Because of the Field of View of the camera the detection is happening at only one particular point instead of whole plant

Foreword Prospect

- Expansion to Other Crops or other vegetables, fruits and flesh
- Extending the application for Household appliances – zero-wastage
- Improved Machine Learning Models
- Connecting Multiple machine Learning Devices
- Expanding the idea on to real field application

References

- JETIR : IoT-based Smart Plant Monitoring System Using Nodemcu
- Design of an Artificial Intelligence of Things Based Indoor Planting Model for Mentha Spicata (Hao-Hsiang Ku 1, Cheng-Hsuan Liu and Wen-Cheng Wang)